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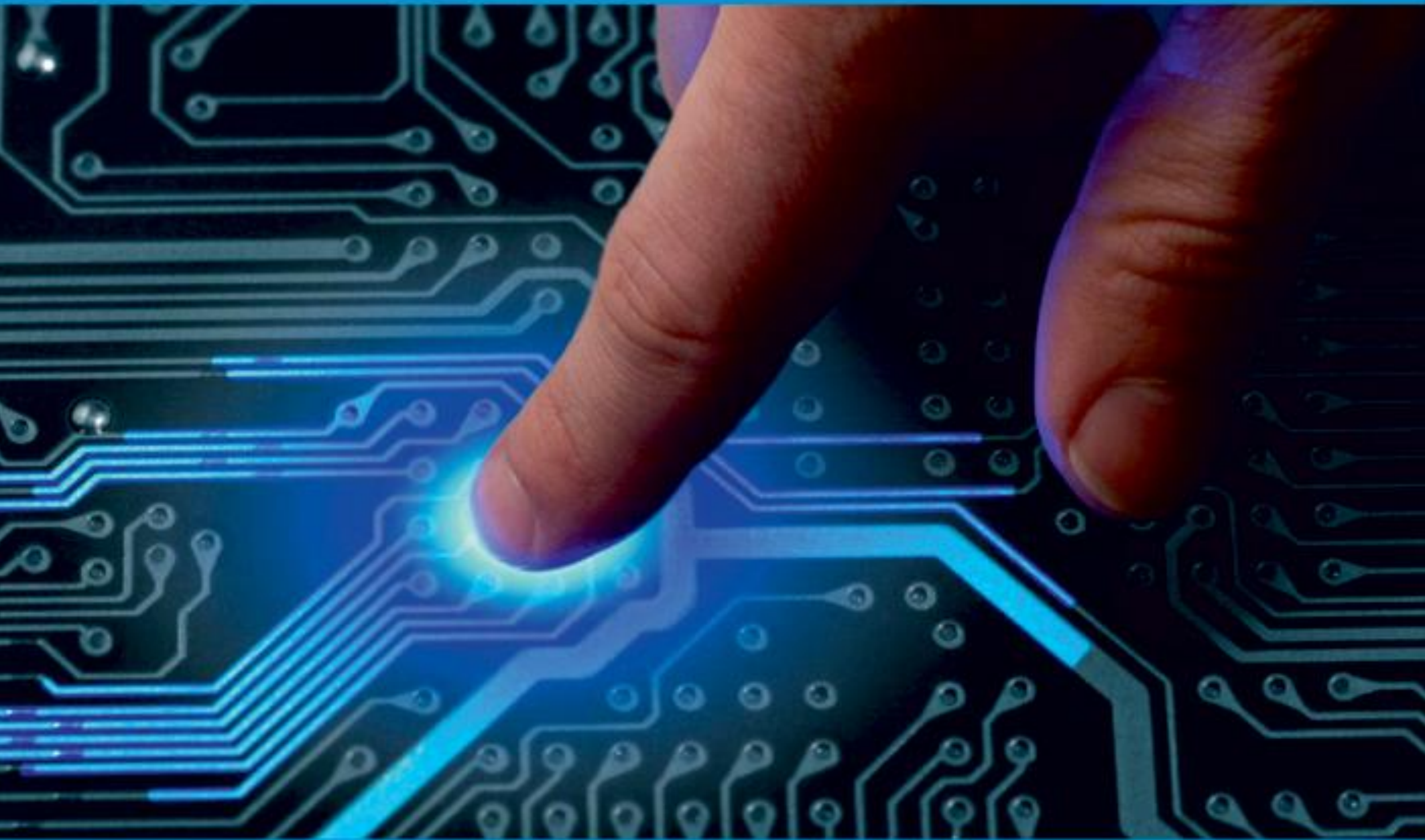

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Deep Learning Model for Classification and Grading of Glaucoma

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ABSTRACT: Glaucoma is an irreversible neurodegenerative disease, where intraocular hypertension is developed due to the increased aqueous humor and blockage of the drainage system between the iris and cornea. As a result, the optic nerve head, which sends visual stimulus from our eyes to the brain, is damaged, causing visual field loss and ultimately blindness. Glaucoma is considered as the sneak thief of vision because it is difficult to diagnose early, and its regular screening is highly recommended to distinguish the neurological disorder. The detection of glaucoma is costly and time-consuming and not only there always remains a good possibility of human error but also this detection method is dependent upon the availability of the resources (experienced ophthalmologists and expensive instruments). The major goal of this proposed work is to build a deep learning model to diagnose glaucoma and automatically grade the stages of glaucoma depending on its severity.

KEYWORDS: Glaucoma; neurodegenerative disease; intraocular hypertension; optic nerve head; visual field loss; sneak thief of vision; ophthalmologists: deep learning model; diagnose; grade.

I. INTRODUCTION

Glaucoma is a group of eye conditions that damage the optic nerve. The optic nerve sends visual information from the eye to the brain and is vital for good vision. Damage to the optic nerve is often related to high pressure in the eye. But glaucoma can happen even with normal eye pressure. Glaucoma can occur at any age but is more common in older adults. It is one of the leading causes of blindness for people over the age of 60. Many forms of glaucoma have no warning signs. The effect is so gradual that one may not notice a change in vision until the condition is in its later stages. The retina is a multi-layered structure that covers a large surface inside the eye. The function of the retina is to convert light to a neural response for further use by the brain. The retina contains two different types of photoreceptors: rods and cones. A healthy eye consists of around 60 million rods and around 3 million cones. Rods are located at the peripheral part of the retina, they are responsible for peripheral vision, motion detection and the perception of light/dark contrast. Cones are mostly located in the macula luteal region of the retina, with most of the cones living at the central part of the macula lutea, the fovea centralis. The optic nerve transmits electrical impulses from the eyes to the brain. It is made of more than a million tiny nerve fibers. It is like an electric cable made up of many small wires. As these

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nerve fibers die, the patient will develop blind spots in the vision. The patient may not notice these blind spots until most of the optic nerve fibers have died. If all of the fibers die, patient will become blind.

Glaucoma is an optic nerve head condition caused by excessive fluid pressure in the eye. Glaucoma develops when the eye's drainage mechanism becomes clogged, allowing fluid to pool in the eye and produce pressure [1]. Glaucoma is caused by high intraocular pressure, it is more likely to develop in persons who have a family history of the disease and people who have specific eye disorders such as diabetes or short-sightedness, are more prone to develop the disease. The most important effect of this disease is the loss of vision and sometimes this effect might become permanent. Glaucoma is generally found in people over age above 60. There are several causes due to which glaucoma is found, they can be poor or reduced blood flow to the optic nerve of the eye and sometimes due to the blocked or restricted drainage in the eye. Sometimes people who commonly use eye drops or medications, such as corticosteroids have more chances to get affected by this disease

Deep learning is a subset of, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behaviour of the human brain. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding humanlevel performance. Deep learning techniques have been recently demonstrated to yield highly rep-resentations that have aided in many computer vision tasks. For example, Convolutional Neural Networks (CNNs) have obtained the significant improvements in image classification and object segmentation [9].

A pre-trained model is a saved network that was previously trained on a large dataset, typically on a large-scale image-classification task. We can either use the pre-trained model as is or use transfer learning to customize this model to a given task. The intuition behind transfer learning for image classification is that if a model is trained on a large and general enough dataset, this model will effectively serve as a generic model of the visual world. We can then take advantage of these learned feature maps without having to start from scratch by training a large model on a large dataset.

Transfer learning is a machine learning technique that involves using a pre-trained model as a starting point for a new task, rather than training a new model from scratch. The pre-trained model is typically trained on a large dataset for a related task, such as image classification, and the weights and parameters of the pre-trained model are used as the initial weights for the new task. This allows the new model to benefit from the general features learned by the pre-trained model, rather than starting from random initialization.

III. LITERATURE SURVEY

With the use of transfer learning and deep learning techniques, Serener and Serte [3], presented deep learning algorithms to classify early and advanced glaucoma on fundus images. This classification's accuracy performance for ResNet50 is 86 percent, while its accuracy performance for the GoogLeNet model is 85 percent. The model's downside was that it was less accurate than other methods for detecting Glaucoma illness. To improve accuracy, the models can be substituted with alternative CNN (Convolutional Neural Network) models.

The estimation of people who have been affected with Glaucoma disease worldwide under age groups, Rohit Varma, et al.‟s [4] found to reintegrate epidemiologic data with some of the economic and individual pressure of glaucoma which highlights the cause of glaucoma on individuals, health systems, and societies. The prevalence of POAG (Primary Open - Angle Glaucoma), is considered to be 16 times greater among those people aged 80 years compared to those aged between 40 to 49 years and 13 times higher than those aged 50 to 59 years. The disadvantage of this approach was that glaucoma therapy was extremely cost effective when diagnostic costs were omitted and optimistic treatment efficacy assumptions were applied.

J. Ayub, et al. [5], highlights the treatment of glaucoma disease by utilizing cup and disc segmentation using RGB (Red, Green & Blue) and HSV (Hue - Saturation Value) color models with K-mean Clustering Techniques. This approach has an accuracy rate of 86 percent. This model does not account for the circulatory system that runs throughout the disc, which overlaps basically with the precision of detecting the proper segments which belong to the disc.

A. Sallam et al. [6], presented the detection of glaucoma by using Transfer Learning from Pre- trained CNN Models such as Pre-trained AlexNet, VGG11, VGG19, and VGG16 models using Deep learning techniques, with accuracy of 81.4 percent, 80 percent, 82.2 percent, and 80.9 percent on the LAG (Large Scale Attention based Glaucoma) dataset.

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Patil and Nikam [7] presented a MATLAB GUI (Graphical User Interface) for glaucoma identification using fundus images. To diagnose a sickness. Image processing techniques of the CDR (Cup - to - Disc Ratio) type and ellipse methods are utilized. The optic cup and the optic disc's boundaries are detected in this case. The segmentation and the precision of the disc and cup is inefficient.

Dhumane and Patil [8] had presented glaucoma detection automated using CDR by super pixel segmentation. This technique does not require patience at the time of testing as only the retinal image is sufficient by the method of Superpixel Segmentation Techniques. This uses a simple linear iterative clustering algorithm where High Sensitivity values are generated, therefore signifying the role of image based classification. From a minimal number of components, a fully working, affordable, handheld, nonmydriatic fundus camera can be easily made. A camera like this with a combination of transfer learning based web app could be beneficial for a range of healthcare practitioners, especially those who work in places where a standard table-mounted nonmydriatic fundus camera would be uncomfortable and not at all user friendly to carry around.

The Hough transform was shown to be efficient in separating OD in the red channel, as demonstrated by Hagiwara et al. [10]. Vessel displacement was computed using the chessboard metric, and several values were generated that allowed the diagnosis of normal and glaucoma fundus pictures.

A new method was created that analyzes the flow of blood vessels in the optic nerve in order to identify and diagnose glaucoma. Using an intensity threshold, Rathore et al. [11] were able to compute clinical parameters for the first time by splitting the OD and OC.

To segment the OC, thresholding is used using Otsu segmentation. Dey and Dey [12] utilized a randomized Hough transform in combination with a Canny edge detection technique to obtain optical contours in their research.

The creation of a U-Net architecture was to help with the segmentation of OD and OC. This was done by Pandit et al. [13]. U-Net models have CNNs in them, and CNNs are the most vital part of a U-Net model. The latter of the two routes in this configuration grows, while the former shrinks. The contracting route is implemented using the architecture of CNN with resolution layers that work well. The expansion layer resolution is very low. The contracting path‟s image data is merged with the growing path‟s data. U-Net is able to identify patterns at a variety of scales.

A model of attention-based CNN (AG-CNN) for identifying glaucoma was proposed by Li et al. and it was tested on a database known as the large-scale attention-based glaucoma database (LAG). The removal of large levels of redundancy from fundus images may result in a reduction in the accuracy and reliability of glaucoma identification. The AG-CNN model took this into consideration and made a decision on it. In this model, subnets of attention prediction, pathological region localization, and classification were combined to form an overall model. When it comes to detecting glaucoma, the model has an AUC of 0.983. In several cases, the ROI was only partially highlighted, and the minor problematic regions were not correctly identified [14].

III. PROPOSED SYSTEM

The proposed system will identify whether a patient is glaucomatic or not using retinal fundus Image. In the pre-processing stage, the test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy. The test image is fed to the pretrained model to get the prediction metrics after passing through various mathematics-based pictorial manipulation layers. Then predictions are made to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification. This helps in predicting the results. The images which are classified as glaucomatic will be used to measure the severity of glaucoma using another deep learning model. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The predicted results will be generated and displayed in the web app interface.

IV. METHODOLOGY

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. For this project we apply the technique of transfer learning to build the model that can detect glaucoma.

The dataset contains retinal fundus images which are labelled as positive and negative glaucoma. First, the input data is pre-processed to find the images of suitable format, images are resized to suitable height and width, redundant

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data is eliminated and images are standardize and normalized. The training images from dataset are used for transfer learning. The trained model is evaluated by using test images. These steps are repeated for different Image classification models. Performance of each classification model will be compared.

The fundus images which are identified as glaucomatic will be used to check severity of the condition using another deep learning model. This grading model will classify a glaucoma effected fundus image as 'early', 'moderate' or 'severe'.

The trained model with highest performance metrics will be saved and used to deploy into the web application. Retinal fundus image of the patient is collected using a Ophthalmoscopic camera by the doctor. A web application is made available to the doctor where fundus image of the patient can be uploaded. This image will be the input for the trained model and used to diagnose the presence of glaucoma. The image identified as positive will be sent to grading model for severity check. Finally, the results will be saved in a database.

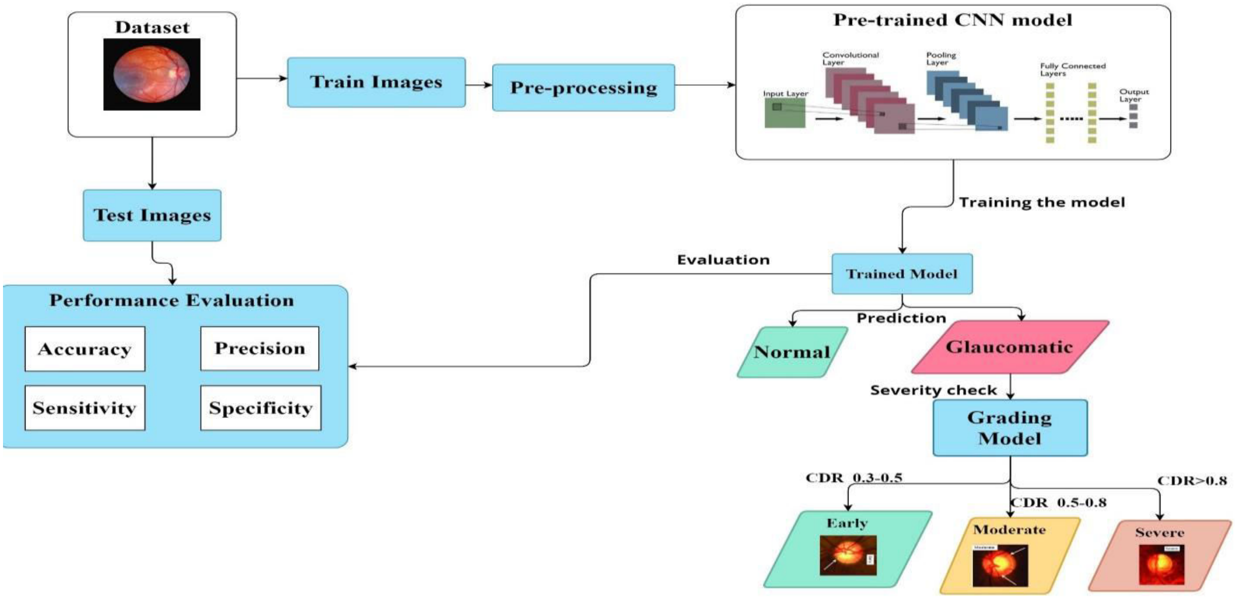

Fig 4.1: Training the Model

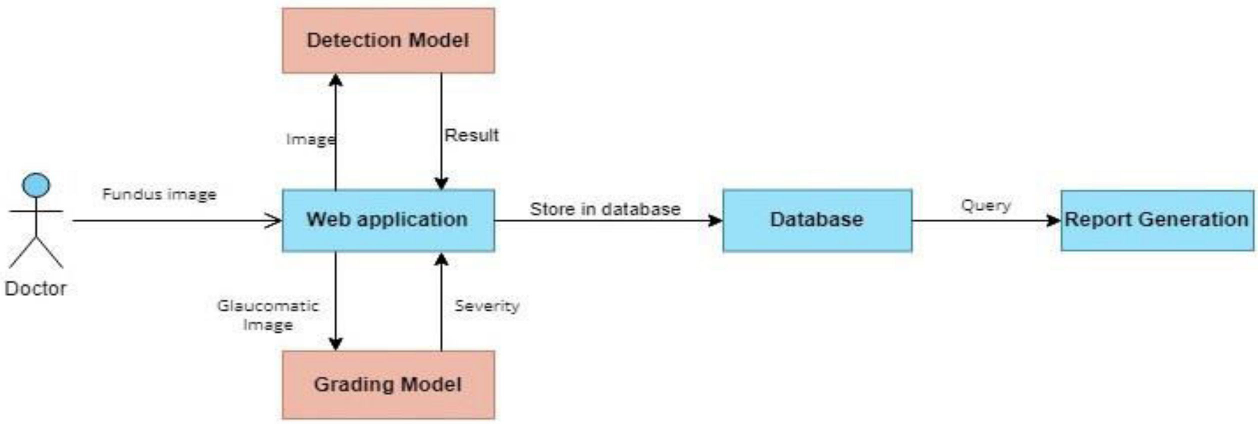

Fig 4.2: Proposed working flow of Web Application

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V. CONCLUSION

This paper is employed to search out to gain knowledge about the glaucoma and its diagnosis to build an efficient method for glaucoma detection. The existing system is repetitive and time consuming and involves use of many devices. To overcome the drawback, we have proposed a system with transfer learning algorithms as these algorithms are more accurate and efficient and also the Deep learning models have shown great promise in the classification and grading of glaucoma. They have the ability to extract features automatically from images, which can help in the detection and monitoring of glaucoma. Convolutional neural networks (CNNs) have been the most widely used deep learning model for glaucoma classification and grading. These models have achieved high accuracy and specificity in detecting glaucoma and classifying its severity.

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